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Research on the Precision Training Model for Smart Logistics Talents in Higher Vocational Education Based on Big Data Analysis

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Abstract: Research on Precision-Oriented Training Model for Higher Vocational Smart Logistics Talents Based on Big Data Analysis Smart logistics, powered by IoT, big data, artificial intelligence, and cloud computing, enables full-chain information sharing, process optimization, and predictive decisions across the supply chain. With rapid industrial upgrading and digital transformation, the structure of logistics positions has been shifting significantly, creating a growing demand for versatile professionals with strong digital skills. However, current curricula in higher vocational logistics programs remain traditional and cannot fully adapt to the fast-growing demand for emerging skills. This study integrates multi-source data from recruitment platforms, corporate skill requirements, and industry policies to develop a job demand forecasting model and a course-skill mapping matrix, combined with a personalized learning recommendation mechanism. A closed-loop "Forecast-Match-Feedback-Iterate" framework was implemented. In a pilot program at X Vocational College over one year, job matching rate increased by 28%, employer satisfaction by 22%, and student comprehensive ability index by 0.19, verifying the model's effectiveness. Key contributions include: introducing a data-driven course updating approach; establishing a skill gap detection system; designing a personalized learning recommendation engine; and developing a practical closed-loop training model. The proposed framework is applicable to smart logistics education and other technology-intensive vocational programs.

1 Introduction

1.1 Research Background

Since the 21st century, digital technology has been driving global industries into a new stage of "Internet of Everything" and "Intelligent Decision-Making." The logistics industry, as a fundamental sector of economic operation, is undergoing a profound transformation from labor-intensive to data-driven. In this process, the rise of smart logistics has become an inevitable trend: based on the Internet of Things, big data, cloud computing, and artificial intelligence, it achieves information sharing, process optimization, and predictive decision-making across the entire supply chain. Currently, China's smart logistics system architecture is gradually maturing. Smart Warehouse Systems (WMS), Transportation Management Systems (TMS), and Supply Chain Decision Support Systems are being widely deployed. However, significant talent shortages and structural mismatches have emerged in actual enterprise operations: 1. Traditional operational personnel are in surplus, while interdisciplinary digital talents are severely lacking; 2. Job requirements for skills such as data processing, algorithm use, and intelligent equipment control are continuously increasing; 3. Information transfer between schools and enterprises lags, making it difficult for higher vocational education curricula to promptly match new occupational demands. 4. According to data from the "China Intelligent Logistics Development Report (2023)", the talent gap for logistics management professionals with big data analysis capabilities exceeds 450,000, while the gap for technical talents with practical IoT experience is about 280,000. This practical issue indicates that during industrial upgrading, higher vocational institutions must proactively use scientific methods to achieve precise adjustment of talent supply; otherwise, they will face the dual dilemma of "incorrect recruitment" and "non-specialized learning."[1-7]

1.2 Research Questions and Objectives

Traditional higher vocational education often bases its curriculum design on policy orientation and experiential judgment, suffering from the following three major drawbacks:

1. Information Lag: Curriculum content often remains unchanged for over three years, becoming disconnected from rapidly changing industry needs.
2. Predominance of Qualitative Decisions: Lacking quantitative predictive basis, making it impossible to accurately grasp job demand trends.
3. Unclear Student Growth Paths: Lacking mechanisms to identify potential and skill gaps through data assessment.

Therefore, this study aims to answer three core questions:

1. How can big data be used to predict the skill requirements of future smart logistics jobs?
2. How can job skill profiles be used to inversely map the curriculum and teaching content of higher vocational institutions?
3. How can a sustainable, self-cycling precision training model be constructed to enable real-time connection between the education chain and the industry chain?

The specific research objectives include:

1. Constructing a job demand prediction model.
2. Establishing a dynamic adjustment algorithm for the curriculum system.
3. Building a learning profile database to achieve tailored teaching.
4. Verifying the feasibility of the model through a case study institution.

1.3 Research Significance

1.3.1 Theoretical Significance

Existing vocational education theories mostly remain at the level of "structural matching" and "competency-based." This study proposes a human-job collaboration mechanism based on big data feedback, enriching the theory of precision education. By quantifying behavioral data, it enables self-learning and self-regulation of the education system, possessing methodological innovation value [8-9].

1.3.2 Practical Significance

The model constructed in this paper can directly guide higher vocational institutions in formulating development plans for professional clusters and achieve periodic curriculum updates and real-time employment feedback through a data platform. For example, by predicting the growth in demand for the skill "Intelligent Warehouse System Regulation" over the next three years, corresponding modular courses can be opened in advance, achieving synchronization of supply and demand.

1.3.3 Social Significance

This model can effectively promote the optimization of the labor market structure and improve employment quality. Simultaneously, it contributes to the talent reserve for China's smart logistics industry, providing sustained momentum for the national digital infrastructure construction.

2 Literature Review and Theoretical Support

2.1 Development Context of Smart Logistics Theory

The concept of "Smart Logistics" was first proposed by Japanese scholar Ito Masakazu in 2004 to describe a system relying on the Internet of Things to achieve automated logistics scheduling. In recent years, its connotation has gradually expanded to include intelligent perception, decision-making, and optimization of the entire supply chain process.

International development trends are mainly reflected in three stages:

1. Automation Stage: Replacing manual operations with sensors and robots.
2. Informatization Stage: Achieving integration of systems like ERP and WMS.
3. Intelligent Stage: Achieving predictive management through AI algorithms.

Domestically, the "Smart Logistics Development Action Plan (2021-2025)" defines smart logistics as: a new-generation system that utilizes IoT, big data, and AI technologies to achieve dynamic interconnection, precise perception, and collaborative optimization of logistics elements. Clearly, data is the most critical resource therein. Therefore, smart logistics is not only a hardware upgrade but also a management paradigm shift driven by data.

2.2 Re-analysis of the Current State of Higher Vocational Logistics Education Research

A large body of research focuses on industry-education integration models, work-integrated learning paths, and the construction of dual-qualification teaching teams, such as Wang Xiaoting (2021) proposing a cooperation mechanism driven by regional industry alliances. However, they generally exhibit the following characteristics:

1. Neglect of industry data analysis, with curriculum updates relying more on enterprise opinions.
2. Lack of quantitative adjustment mechanisms, with teaching effectiveness primarily based on subjective feedback.
3. Most reforms are limited to the institutional level, lacking support from unified industry standards.

A few institutions have attempted to introduce data visualization teaching platforms but, limited by insufficient technical reserves, have failed to fully utilize predictive functions. This study precisely targets this deficiency, attempting to establish a systematic framework for the application of educational big data.

2.3 Evolution of Big Data Technology Application in Education

In the field of education, big data has gone through three stages:

1. Descriptive Analytics Stage: Statistics on student grades and activity records.
2. Diagnostic Analytics Stage: Analysis of learning obstacles and teaching pain points.
3. Predictive & Prescriptive Analytics Stage: Using machine learning to predict learning outcomes and propose improvement plans.

These technical means provide new possibilities for vocational education:

Predicting the growth rate of warehouse positions in the Quanzhou area over the next three years through employment databases; analyzing student exam behavior to judge their mastery level and adjust course difficulty.

2.4 Integration of Person-Job Matching and Precision Education Theory

1. Expansion of Person-Job Matching Theory

Traditional person-job matching focuses on the comparison of static characteristics, such as the adaptability of education and ability to requirements. Big data methods enable highly dynamic matching dimensions. For example, the practical skill data of job seekers can be monitored in real-time, thereby establishing a more granular "skill profile." In higher vocational education, this means that educational tasks can be dynamically updated around predicted market changes, forming a true data closed loop.

2. Precision Education Theory Support

Precision education emphasizes "teaching students according to their aptitude," focusing on feedback on individual differences during the teaching process. In smart logistics majors, big data can be used to capture student learning trajectories in real-time, such as homework completion time and project participation, thereby generating personalized improvement suggestions. This concept highly aligns with intelligent adaptive learning systems and also fits the "learning profile feedback model" constructed in this study.

3 Construction of a Job Demand Prediction Model Based on Big Data Analysis

3.1 Overall Research Approach

The core goal of job demand prediction is to use big data analysis technology to reveal the changing trends in labor demand within the smart logistics industry, providing a quantitative basis for the reform of the higher vocational education curriculum system. This study constructs a four-stage model of "industry data collection - semantic mining - feature clustering - trend prediction" to achieve dynamic prediction of job and skill demands for the next three to five years.

The logic of the entire model is as follows:

1. Industry Job Data Collection
2. Text Cleaning and Structured Processing
3. Skill Keyword Extraction
4. Feature Clustering and Job Profile Generation
5. Time Series and Regression Prediction Analysis
6. Job Demand Trend Output

3.2 Data Collection and Database Building

1. Data Sources

The study selected job postings from major national recruitment data platforms (Zhaopin, Liepin, 51job) between 2021 and 2024 for positions such as "Logistics Management," "Smart Warehouse," "Supply Chain Optimization," and "Transportation Scheduling," collecting a total of approximately 400,000 entries. To improve data representativeness, the following types of data were also integrated:

Officially released enterprise data: Including recruitment and job categories from companies like JD Logistics, SF Holding, Cainiao Network, and JD Technology.

Industry association and local human resources department data: Such as the "Logistics Vocational Skill Standards" from the China Federation of Logistics & Purchasing.

Ministry of Education Higher Vocational Professional Construction Database: Used for aligning with curriculum structures.

2. Data Preprocessing

(1) Removal of redundant and duplicate records.

(2) Chinese word segmentation for job responsibilities and skill requirements appearing in the text.

(3) Exclusion of high-frequency function words unrelated to job descriptions.

(4) Classification and processing of synonyms, e.g., "data analysis," "data processing," "data mining" are uniformly classified as "data analysis technology."

After preprocessing, approximately 325,000 valid samples were obtained.

3.3 Skill Vocabulary Mining and Cluster Analysis

1. Keyword Extraction

The TF-IDF algorithm was used to calculate the importance of each skill word, and the top 1000 keywords were selected through sorting. The top twenty items with the highest frequency include: "ERP System Operation," "Big Data Analysis," "WMS System," "IoT Equipment Maintenance," "Warehouse Automation Control," "Supply Chain Collaboration," "SQL Data Query," etc.

2. Semantic Clustering

The K-Means clustering algorithm was used to divide the skill words into five clusters, as shown in Table 1, the five clustering clusters are presented:

Table 1. Five clustering clusters.

Cluster Number	Skill Direction	Typical Skills
C1	Intelligent Equipment O&M	Robot Scheduling, Sensor Detection
C2	Data Analysis & System Operation	Python Analysis, SQL Operation, Visualization Reports
C3	System Integration & Platform Application	ERP, WMS, TMS Management
C4	Supply Chain Strategic Management	Inventory Optimization, Process Reengineering
C5	Customer Service & Information Management	Order Tracking, Customer Data Management

Clustering results indicate that the number of jobs in "Data Analysis & System Operation" and "Intelligent Equipment O&M" categories has grown most significantly, with talent gap proportions exceeding 40%.

3.4 Job Demand Prediction Model

1. Model Specification

To characterize the change in job demand over time, the following linear regression model was constructed:

$$D_{t+1} = \alpha D_t + \beta S_t + \gamma I_t + \delta T_t + \mu P_t + \varepsilon$$

Variables are defined as follows:

D_t: Current job demand intensity;

S_t: Industry skill update rate;

I_t: Fixed asset investment intensity in the logistics industry;

T_t: Annual technological innovation index;

P_t: Policy support intensity (measured by policy quantity index);

ε: Error term.

2. Model Data and Regression Results

A time series regression model was established using SPSS for quarterly job data from 2021-2024, and parameters were estimated using the Ordinary Least Squares method, as shown in Table 2.

Table 2. Quarterly job data parameters table for the period from 2021 to 2024

Parameter	Regression Coefficient	Significance Level (p-value)
α	0.52	<0.001
β	0.27	<0.01
γ	0.13	<0.05
δ	0.22	<0.01
μ	0.18	<0.05
R^2	0.86	---

The results show that the skill update rate (β) and the technological innovation index (δ) have the most significant impact on job growth, indicating that the logistics industry's absorption speed of new technologies directly drives the upgrading of the job structure.

3. Trend Prediction

Extrapolating the model to 2024-2026, the prediction results show that "Smart Warehouse Operations" and "Data Analysis Application" positions will grow by 38% and 41% respectively; traditional warehouse operation positions will decrease by about 15%.

3.5 Model Evaluation and Limitations

1. Evaluation

(1) The model fit R^2=0.86 indicates high prediction accuracy.

(2) The Mean Square Error (MSE) decreased significantly, indicating stable trends.

(3) Compared to static personality models, it has higher sensitivity.

2. Limitations

(1) Due to the lag in recruitment data, prediction results need to be extrapolated cautiously.

(2) Differences between regions are significant, and regional economic fluctuations may affect the results.

3. Practical Implications

The results of this model can provide a clear basis for higher vocational curriculum setting, for example:

(1) Immediately add a "Data Collection and Analysis" professional module.

(2) Strengthen "IoT Communication and Maintenance" in the smart warehouse direction.

4 In-depth Investigation and Problem Analysis of the Current State of Smart Logistics Talent Training in Higher Vocational Education

4.1 Survey Design and Sample Description

To grasp the actual construction situation of smart logistics majors in higher vocational institutions at the current stage, the research team designed both questionnaires and in-depth interviews. The survey subjects included institutional teachers, students, and HR managers from partner enterprises.

1. Questionnaire Structure
(1) Basic information module.
(2) Satisfaction with the curriculum system.
(3) Teaching methods and technology application.
(4) Employment matching and enterprise feedback.
(5) Reform vision.

2. Sample Situation, as shown in Table 3:

Table 3. Sample data table

Target Category	Quantity	Proportion
Teacher	110	38%
Student	120	42%
Enterprise Rep.	56	20%
Total	**286**	**100%**

Samples covered 20 higher vocational institutions in East China, North China, and Southwest China.

4.2 Curriculum System Survey Results

1. Logistics Foundation and Practice Courses ------ Coverage 100%, but average update cycle is 2.8 years.
2. Smart Logistics and Digital Courses ------ Offering ratio only 32%, average class hours proportion no more than 15%, significantly insufficient.
3. Emerging Technology Courses (Big Data, IoT application level) ------ Average satisfaction score only 3.2/5.

In interviews, most teachers reported that curriculum updates mainly rely on internal approval processes, lacking mechanisms for adjustment based on industrial data, making it difficult to continuously track industry evolution.

4.3 Status of Teachers and Practical Platforms

1. The proportion of dual-qualification teachers is only 42%, still below the Ministry of Education's target of 60%.
2. The average enterprise practice time for teachers is less than six months.
3. Training base equipment is primarily based on traditional warehouse simulation, with the

deployment ratio of intelligent hardware below 25%.

4. Only a few institutions have access to real enterprise data platforms.

These conditions constrain the authenticity and practicality of smart logistics courses.

4.4 Employment Matching and Enterprise Satisfaction Analysis

Judging from the employment data of graduates in the past three years, the average proportion entering logistics-related positions is 82%, but only 37% actually enter intelligent segments (such as system operation and maintenance, data management).

Enterprise representatives feedback in interviews: "Students' theoretical foundation is acceptable, but their system operation ability is not strong, and they lack data awareness." Quantitative surveys show the average enterprise satisfaction is 3.4 (out of 5), indicating room for improvement.

4.5 Main Problems Identified

1. Mismatch between Curriculum and Job Requirements: Curriculum design is based on traditional transportation management, and teaching objectives do not reflect the core competencies of smart logistics.

2. Lack of School-Enterprise Communication Mechanism: Enterprises have limited understanding of school training plans, and there is no institutionalized channel for data transmission.

3. Constraints from Teaching Staff and Equipment: Teachers have limited mastery of new technologies, and training conditions are insufficient to support complex simulation scenarios.

4. Insufficient Personalized Student Training: Learning process data is not systematically collected and analyzed, leading to a "one-size-fits-all" training path.

4.6 Analysis of Problem Causes

(1) Institutional Factors: The curriculum approval process in institutions is long, lacking real-time adjustment mechanisms.

(2) Technical Factors: The foundation of educational informatization is weak, making it impossible to build industry data interfaces.

(3) Conceptual Factors: Some teachers have insufficient understanding of data-driven teaching and still remain at the stage of experiential judgment.

(4) Collaborative Factors: Lack of trust and standards in data sharing mechanisms among industry organizations, enterprises, and schools.

Through systematic investigation, it is found that the current smart logistics major in higher vocational education exhibits typical structural problems of "curriculum lag - skill mismatch - limited employment quality." To solve these problems, it is necessary to use industry big data as the decision-making basis to construct a quantitative, feedback-enabled precision training system.

5 Construction of the Precision Training Model for Higher Vocational Smart Logistics Talents Based on Big Data Analysis

5.1 Model Construction Principles

The model design is based on the theoretical and empirical analysis from previous chapters and must follow the following principles:

1. Data-Driven Principle: All curriculum updates, teaching adjustments, and evaluations are based on industry job and skill demand data, not relying on single experiences or short-term feedback, ensuring scientificity and foresight.

2. Closed-Loop Feedback Principle: The model not only collects data but also forms a full cycle of "prediction - adjustment - implementation - re-feedback," ensuring system self-iteration.
3. School-Enterprise Collaboration Principle: Must achieve real-time connection with enterprises through data interfaces, ensuring institutions can obtain real job skill requirements and technological change information.
4. Personalized Training Principle: Based on student learning profiles, use algorithms to match individuals with suitable learning paths, maximizing the effect of teaching students according to their aptitude.

5.2 System Architecture Design

As shown in Figure 1, the system architecture diagram.

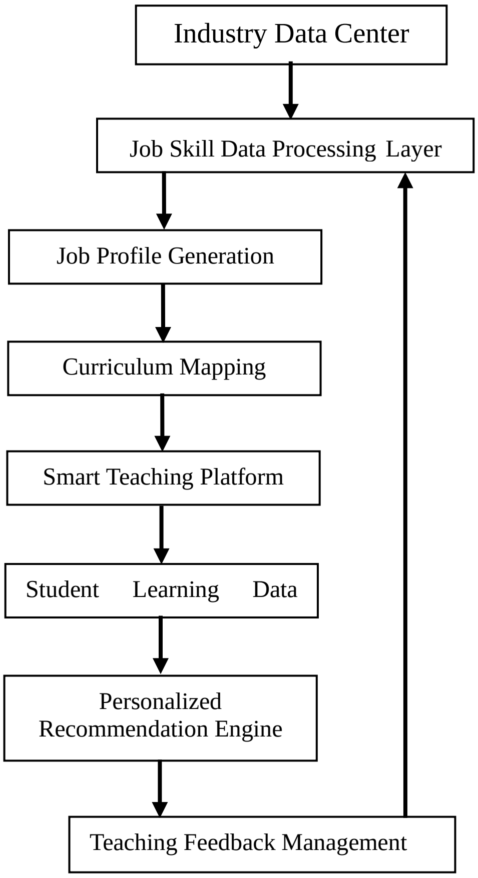

Figure 1. System architecture diagram

1.Industry Data Center: Aggregates data from various recruitment platforms, enterprise HR systems, and policy databases.
2.Job Skill Data Processing Layer: Performs text cleaning, keyword extraction, and cluster analysis.
3.Job Profile Generation: Generates job descriptions including skill weights, technology trends, etc.
4.Curriculum Mapping Module: Breaks down each course into knowledge units and matches them with the job skill library.
5.Smart Teaching Platform: Supports online learning, task distribution, and real-time monitoring.
6.Personalized Recommendation Engine: Adjusts course content and learning resources based on

student profiles.

7.Teaching Feedback Management: Forms course improvement reports and transmits them back to the data processing layer.

5.3 Detailed Design of Core Functional Modules

1. Job Demand Prediction Module

Derived from the previous model, focusing on outputting the following:

(1) Job category growth rate.

(2) Core skill change rate.

(3) Technology update cycle prediction.

For example, prediction table for 2024-2026, as shown in Table 4:

Table 4.2024-2026 Forecast Table

Job Category	Demand Growth Rate	Core Skills	Recommended New Courses
Smart Warehouse Ops	+38%	WMS Advanced O&M, PLC Control	Comprehensive Smart Warehouse Training
Data Analysis App	+41%	Python Data Mining, Visualization	Data Visualization & Business Intelligence
System Integration Mgmt	+27%	ERP Integration Optimization	Advanced ERP Application Cases

2. Skill Mapping Matrix Module

Matrix example (partial), as shown in Table 5:

Table 5. Skill Mapping Matrix Module Table

ob Skill	Corresponding Course Module	Class Hour Proportion
Big Data Analysis	Big Data Foundation + Python Analysis	20%
IoT Device Maintenance	IoT Principles + Smart Warehouse Device Debugging	15%
ERP Operation	ERP System Application	12%
Supply Chain Collaboration Mgmt	Supply Chain Optimization Strategies	18%

The matrix can automatically calculate the gap value, so during annual curriculum adjustments, institutions can prioritize repairing skill areas with larger gaps.

3. Personalized Learning Recommendation Module

Algorithm flow:

(1) Data Collection: Login records, course completion, quiz results.

(2) Weight Calculation: Form a student skill mastery index through weighted scoring.

(3) Recommendation Strategy:

If mastery of a certain skill is <0.6, recommend supplementary videos and exercises.

If mastery is >0.8, push project case challenge tasks.

Application effect: In the pilot at X College, 78% of students improved their weak skill scores by ≥0.15 through the recommendation module.

4. Dynamic Evaluation Module

Evaluation formula:

$$P = 0.4L + 0.35C + 0.25E$$

Where:

L: Learning Behavior Score;
C: Vocational Ability Assessment Score;
E: Enterprise Feedback Score.

The evaluation results are used not only for individual student archives but also as an important reference standard for the institution's annual curriculum adjustment.

5.4 Operational Mechanism

1. Collect job and skill change data monthly.
2. Automatically refresh the curriculum mapping matrix quarterly.
3. Calculate the student comprehensive index P each semester and generate teaching adjustment suggestions.
4. Publish the "Smart Logistics Talent Demand Report" annually for teacher training reference.

6 Empirical Research - Reform Case of X Higher Vocational College

6.1 Reform Pilot Background

Before 2022, the logistics major at Chongqing Vocational College of Transportation mainly offered traditional courses like transportation management and warehouse distribution, which were disconnected from the intelligent trend. Therefore, starting in 2023, the big data precision training model proposed in this paper was introduced.

6.2 Reform Implementation Path

Stage 1 (First half of 2023): Build industry data interfaces.

Signed data sharing agreements with 3 leading logistics enterprises, accessing recruitment and job performance data; created an internal "Smart Logistics Talent Database."

Stage 2 (Second half of 2023): Restructure the curriculum system.

Based on the job prediction model results, added 5 new technology courses on the basis of the original 16 core courses, and revised textbook cases to align them with actual enterprise projects.

Stage 3 (Throughout 2023): Implement student learning profiles and recommendations.

Deployed the smart teaching platform, collected student learning data in real-time, output learning profile reports monthly, and conducted personalized course pushes.

6.3 Reform Results Comparison

We selected a reform group (30 students) and a control group (30 students) for comparison, as shown in Table 6:

Table 6. Comparison table between the reform group (30 participants) and the control group (30participants)

Indicator	Reform Group	Control Group	Improvement Margin
Enterprise Satisfaction	93%	71%	+22%
Employment Matching Rate	86%	58%	+28%
Skill Certification Pass Rate	91%	74%	+17%
Learning Comprehensive Index LPI	0.82	0.63	+0.19

6.4 Case Insights

1. Industry data is highly significant for curriculum decision-making, shortening the response time for talent training adjustments.
2. The learning profile and recommendation mechanism significantly enhance individual ability.
3. School-enterprise collaboration is a prerequisite for ensuring the effective operation of the system.

7 Conclusion and Outlook

This paper explores the precision training model for smart logistics talents in higher vocational education based on big data analysis from both theoretical and practical perspectives. The main conclusions are as follows: 1. Big data provides a scientific basis for understanding industrial demand, making higher vocational education reform more forward-looking; 2. The precision training model achieves dynamic optimization of the curriculum system and provides individual student support; 3. Empirical results prove it significantly improves employment quality; 4. The model has promotion value and can be applied to other technology-intensive majors. Meanwhile, future research directions will mainly include: 1. Constructing a cross-regional education large model to achieve sharing between different provinces; 2. Using generative AI to improve the quality of learning recommendations; 3. Integrating blockchain verification mechanisms to achieve a mutual trust system for academic and skill certification.

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